1 Introduction

The incidence of the prostate carcinoma is one of the highest in men in the western world [41]. Its position in cancer mortality statistics is also among the highest [7, 35, 36]. The prevalence found at autopsy suggests that the prostate carcinoma is the most common malignancy in human beings in the United States [43].

The different types of diagnostics that are used today (digital rectal examination, transrectal ultrasound imaging and prostate-specific antigen (PSA) value analysis) lack reliability and are therefore not sufficient. Even a combination of these three methods is not sufficient [43, 50, 1].

An automated classification system for prostate diagnostics based on multifeature tissue characterization is proposed. RF ultrasonic echo data is acquired during the standard transrectal ultrasound imaging examination. Several parameters are calculated and fed into two fuzzy inference systems (FIS) working in parallel. The outputs of the FIS are fed into a post processing procedure evaluating contextual information before being combined to form a malignancy map, in which areas of high cancer probability are marked in red. The malignancy map is presented to the physician during the examination to approve the early detection of prostate cancer.

During the last years, studies have been carried out dealing with the characterization of prostate tissue using ultrasound imaging. Some approaches are based on video or image data [3, 21, 17, 32, 33] and do not take into account the depth dependent diffraction and attenuation [21, 17, 32, 33]. Some authors tried to characterize prostate tissue by using only a single parameter, e.g. attenuation estimates [24, 25] or backscatter estimates or by combining different parameters using a lin-
ear approach or a nearest-neighbor technique [10, 11]. Some authors used nonlinear methods like neural networks [12, 13, 14, 2] and Kohonen maps [47] to combine the parameters and even compare different nonlinear methods with each other [34, 49]. An overview of ultrasonic tissue characterization in general can be found in [53, 6]. An overview of prostate diagnostics using ultrasound imaging is given in [50].

By using video data instead of RF data only a small set of analysis parameters can be calculated which do not contain enough information needed to classify the tissue with sufficient accuracy. Only the use of Radio-frequency (RF) data can provide the information used to calculate spectral parameters that characterize prostate tissue in an adequate way.

To prove this statement, two approaches are described in this work. The first approach is based on spectral and texture parameters, while the second approach, which is presented for comparison, only uses texture parameters.

As different parameters have a highly nonlinear interdependence, only a nonlinear model is able to combine the parameters and thus lead to reliable results [47, 32, 33, 26]. For this reason a neuro fuzzy inference system is used in this approach [58, 59, 22, 37, 16].

For the evaluation of parameters the compensation of depth dependent diffraction and attenuation effects has been found to be essential [40, 20, 30, 31, 49, 47, 39].

Some former works focus merely on the evaluation of one set of parameters, e.g. coocurrence parameters [3] or spectral parameters [10, 11, 12, 2]. Other works try to combine the results of different sets of parameters [34, 49, 47, 48]. As the information of parameters of different sets is highly uncorrelated, the combination of parameters originating from different sets might lead to better classification results. From our point of view only a combination of different sets of parameters can provide the classification system with enough information to support a precise decision.

During the search for the best parameters it was found, that for a given depth of the ultrasound echo signal certain parameters perform better than others. This observation leads to the integration of some morphological descriptors, which serve as so-called morphological parameters describing the position of the regions of interest (ROI) within the prostate.

2 Methods

2.1 Data Acquisition and Preprocessing

RF ultrasonic echo data of the prostate is captured during the regular examination of the patient with standard ultrasound imaging equipment (Kretz Combison 350, transrectal probe VRW177AK). Patient compliance is high, as the new method does not extend the normal examination time when applying transrectal ultrasound imaging. The system is operator-independent, which means that no special knowledge or training is necessary for a successful application of the system. The RF data is captured from the ultrasound imaging system before being processed by the ultrasound imaging system’s time gain control unit (TGC). The signal is fed into a custom-made hardware TGC with a known transfer function to compensate for depth dependent attenuation effects and to provide the following analog to digital converter (ADC) with a signal that uses the whole possible conversion range throughout the sampling time. After time variant amplification the data is directly transmitted to a PC and sampled at 33 MHz and 12 bits. During the next step, every A-line is compensated for the induced TGC amplification. Every data frame is subdivided into up to 1000 ROIs per prostate slice using sliding window technique, in order to attain spatially distributed tissue characterization images. Each ROI comprises an area of approximately 3.0 mm × 3.5 mm in diameter at a depth of 20 mm. The smallest lesion that can be detected by the system thus covers approximately 0.1 cm². The ROIs consist of 128 sample points in the transducers axial direction and 16 scan lines in the lateral direction. For attenuation measurements, adjacent ROIs are combined for each single estimation, as the ROI sizes mentioned above are too small to support a reliable attenuation estimation [49]. Their axial and lateral overlap is 75 % and 50 % respectively. Up to five datasets at different transducer positions are being recorded per patient.

The RF data is compensated for system and depth dependent effects using the system’s point spread function over depth as an inverse filter within the system’s effective bandwidth. Using this approach, it is possible to compensate partly for the system’s effects due to focusing and for the electromechanical characteristics of the transducer [53].

2.2 Parameter Extraction

Several parameters are calculated for each ROI. The authors do not claim the extracted parameters to be totally independent of the ultrasound imaging equipment. The parameters used for classification are calculated from the frequency domain and from the time domain, partly before and partly after demodulation [56].

Overall, this approach is based on two parameter groups. The first group consists of spectral parameters, whereas the second group consists of texture parameters of first and second order.

Spectral parameters are calculated after converting the resultant power spectrum to dB [37]. Spectra of each scan line are averaged to form an estimate of the average power spectrum [29, 51]. The primary set of spectral parameters consists of four measures of backscatter calculated for the signal bandwidth. The parameters used in this approach are: slope, axis intercept, midband value and deviation of the linear regression spectrum fit [34, 44, 45, 46, 12]. The measures of backscatter are compensated for attenuation effects us-
ing an attenuation estimation model, which is based on
the multi narrow band method [47, 5, 40, 52]. Three
measures of this attenuation model are also included
in the system. The attenuation parameters used in this
approach are: slope, axis intercept and midband value.
Classification results of the spectral parameters are
given in Table 1.

<table>
<thead>
<tr>
<th>Spectral parameters</th>
<th>P1</th>
<th>P2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Backscatter parameters:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Axis intercept</td>
<td>$A_2$</td>
<td>$A_2$</td>
</tr>
<tr>
<td>Slope</td>
<td>$0.590$</td>
<td>$0.014$</td>
</tr>
<tr>
<td>Midband value</td>
<td>$0.558$</td>
<td>$0.007$</td>
</tr>
<tr>
<td>Square deviation</td>
<td>$0.512$</td>
<td>$0.001$</td>
</tr>
<tr>
<td>Normalized sq. dev.</td>
<td>$0.568$</td>
<td>$0.008$</td>
</tr>
<tr>
<td>Attenuation estimates:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Axis intercept</td>
<td>$0.612$</td>
<td>$0.005$</td>
</tr>
<tr>
<td>Slope</td>
<td>$0.548$</td>
<td>$0.018$</td>
</tr>
<tr>
<td>Midband value</td>
<td>$0.583$</td>
<td>$0.003$</td>
</tr>
<tr>
<td>Group classification</td>
<td>$0.773$</td>
<td>$0.005$</td>
</tr>
</tbody>
</table>

Table 2: Classification results of first order texture parameters for both groups, P1 and P2, and both approaches, FIS and MDC, in comparison. The area $A_2$ under the ROC-curve is given next to the standard deviation $\sigma$ of the estimates. Parameters that were used in the final systems are highlighted.

<table>
<thead>
<tr>
<th>First order texture parameters</th>
<th>P1</th>
<th>P2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FIS</td>
<td>MDC</td>
</tr>
<tr>
<td>Minimum</td>
<td>$0.604$</td>
<td>$0.026$</td>
</tr>
<tr>
<td>Mean value</td>
<td>$0.622$</td>
<td>$0.023$</td>
</tr>
<tr>
<td>Ratio of squares</td>
<td>$0.590$</td>
<td>$0.012$</td>
</tr>
<tr>
<td>Signal to noise ratio</td>
<td>$0.692$</td>
<td>$0.013$</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>$0.528$</td>
<td>$0.010$</td>
</tr>
<tr>
<td>Contrast/Variance</td>
<td>$0.526$</td>
<td>$0.009$</td>
</tr>
<tr>
<td>Full width at half max</td>
<td>$0.528$</td>
<td>$0.004$</td>
</tr>
<tr>
<td>Entropy</td>
<td>$0.510$</td>
<td>$0.004$</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>$0.519$</td>
<td>$0.006$</td>
</tr>
<tr>
<td>Skewness</td>
<td>$0.538$</td>
<td>$0.004$</td>
</tr>
<tr>
<td>Group classification:</td>
<td>$0.681$</td>
<td>$0.016$</td>
</tr>
</tbody>
</table>
Ultrasonic Tissue Characterization for Prostate Diagnostics

Under certain circumstances, some parameters used in this approach may lead to unreliable results. For example, attenuation measurements fail, if data is taken from a region behind calcifications. Some cooccurrence parameters that are independent of the mean intensity still yield satisfying results under these circumstances. Because calcifications are, in most cases, found in the lower section of the prostate, this observation led to the inclusion of morphological descriptors, thus allowing the fuzzy inference system to choose different parameter combinations for different positions. Morphological descriptors that are used in this approach are: distance of the ROI from the center of the ultrasound probe, normalized axial position of the ROI within the prostate and normalized lateral position of the ROI within the prostate. All parameters are normalized for the size of each individual prostate to yield a value between 0 and 1.

Initial results have shown that only a combination of spectral and texture parameters leads to adequate classification results [34, 47, 48].

2.3 Training procedure

Methods for estimating the accuracy of diagnostic tests require independence of the test results in the samples. For this reason, five-fold cross validation methods have been used for the selection and combination of parameters for the final tissue characterization system. Cross validation methods are known to yield a nearly unbiased prediction error, when accepting the disadvantage that the results can be highly variable [8]. In approaches where there are multiple cases from the same patient, estimation and inference of the accuracy of the diagnostic test must account for intraclass correlation. To account for intraclass correlation, the five-fold cross validation method has been used on five datasets, which were constructed considering a division of the amount of patients, not the amount of ROIs [38]. When using cross validation methods and not keeping in mind that possible intraclass correlations are apparent, the classification results will be far from reality as too positively weighted.

2.4 Selection of parameters

During the preselection procedure of parameters for the training process of the system, parameter vectors that are highly linearly dependent on each other are found and discarded using covariance matrix analysis. Parameter vectors that have a small influence on the classification procedure are found and discarded using single classification. During the preselection, the number of parameters is reduced to 13 for the first fuzzy inference system and to 10 for the second system, respectively, using a stepwise selection algorithm based on hypothesis testing. The parameter selection procedure starts by calculating the classification power of each single feature. In order to use a decision-based criterion [28] instead of an approximation-based criterion (e.g. mean square error) as used in other approaches, the classification power is expressed as the area $A_z$ under the ROC-curve [27].

As the number of ROIs used in this work is high (about 170,000), using up to 13 parameters for the classification procedure is still a safe approach [15, 42, 4]. The „curse of dimensionality“ does not account for the settings of this approach, but it has to be considered, that, as several ROIs in this approach result from the same patients, the effective sample size is somewhere between the actual sample size and the number of patients.

<table>
<thead>
<tr>
<th>Second order texture parameters</th>
<th>FIS $A_z$</th>
<th>$\sigma$</th>
<th>FIS $A_z$</th>
<th>$\sigma$</th>
<th>MDC $A_z$</th>
<th>$\sigma$</th>
<th>MDC $A_z$</th>
<th>$\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Angular second moment</td>
<td>0.596</td>
<td>0.014</td>
<td>0.596</td>
<td>0.015</td>
<td>0.519</td>
<td>0.021</td>
<td>0.532</td>
<td>0.023</td>
</tr>
<tr>
<td>Contrast</td>
<td>0.640</td>
<td>0.020</td>
<td>0.639</td>
<td>0.021</td>
<td>0.507</td>
<td>0.018</td>
<td>0.500</td>
<td>0.016</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.537</td>
<td>0.022</td>
<td>0.535</td>
<td>0.022</td>
<td>0.533</td>
<td>0.019</td>
<td>0.540</td>
<td>0.031</td>
</tr>
<tr>
<td>Dimension</td>
<td>0.642</td>
<td>0.020</td>
<td>0.641</td>
<td>0.021</td>
<td>0.510</td>
<td>0.019</td>
<td>0.519</td>
<td>0.012</td>
</tr>
<tr>
<td>SNR</td>
<td>0.598</td>
<td>0.015</td>
<td>0.595</td>
<td>0.015</td>
<td>0.518</td>
<td>0.020</td>
<td>0.532</td>
<td>0.023</td>
</tr>
<tr>
<td>Inverse difference moment</td>
<td>0.609</td>
<td>0.017</td>
<td>0.609</td>
<td>0.018</td>
<td>0.505</td>
<td>0.014</td>
<td>0.519</td>
<td>0.013</td>
</tr>
<tr>
<td>Kappa</td>
<td>0.610</td>
<td>0.023</td>
<td>0.609</td>
<td>0.023</td>
<td>0.629</td>
<td>0.008</td>
<td>0.530</td>
<td>0.009</td>
</tr>
<tr>
<td>Peak Density</td>
<td>0.576</td>
<td>0.016</td>
<td>0.576</td>
<td>0.016</td>
<td>0.510</td>
<td>0.018</td>
<td>0.528</td>
<td>0.018</td>
</tr>
<tr>
<td>Variance</td>
<td>0.596</td>
<td>0.014</td>
<td>0.595</td>
<td>0.015</td>
<td>0.521</td>
<td>0.023</td>
<td>0.532</td>
<td>0.023</td>
</tr>
</tbody>
</table>

Table 3. Classification results of second order (cooccurrence) texture parameters for both groups, P1 and P2, and both approaches, FIS and MDC, in comparison. The area $A_z$ under the ROC-curve is given next to the standard deviation $\sigma$ of the estimates. Parameters that were used in the final systems are highlighted.
2.5 Fuzzy Inference Systems

Two FIS working in parallel classify and separate the ROIs into two classes (negative = benign, positive = malignant). Fundamentals of fuzzy logic and the idea behind this approach can be found in [58, 59, 37]. An overview of neuro-fuzzy systems is given by Jang in [23]. The mathematical background, especially the learning process of the FIS, is also described best by Jang in [23].

The fuzzy output maps of both fuzzy inference systems are transformed into binary maps applying a separation-threshold to separate into two classes. The separation-threshold can be chosen freely by the operator, as the implemented system is a quantitative system. Certainly, an amount of “information” is discarded during this step, but the output of the system becomes more readable by the physician. A following morphological analysis combines clusters in the binary output maps of the fuzzy inference systems to mark areas of similar tissue characteristics. The clustering procedure is implemented by two-dimensional filtering the binary output maps with symmetric 1/0-kernels of systematically determined size. During the training procedure, the optimal kernel sizes and filter-thresholds are determined. This is done by systematically varying kernel sizes and filter-thresholds and comparing the classification results to find the optimal combinations. The optimal kernel sizes and filter-thresholds are determined for the whole range of separation-thresholds, thus still allowing a free choice of separation-threshold during the evaluation procedure. Next to improving the classification rates by a small amount, this post-processing step makes the malignancy maps more readable by the physician.

The results of the two fuzzy inference systems are combined to build a so-called malignancy map, which consists of a conventional B-mode image, in which areas of high cancer probability are marked in red (white on printed matter). The malignancy map (Fig. 1) is presented to the physician during the examination on a PC screen and thus can support the existing methods of diagnostics. Malignancy maps can easily be printed or archived for biopsy planning.

3 Clinical study

During a clinical study, radio-frequency ultrasonic echo data of 100 patients undergoing clinical examinations was recorded. At the day of the examination the youngest patient was 48 years old, the oldest 79 years. Both, the mean and median age of the patients were 64 years. All patients of this study underwent radical prostatectomy. Prostate slices with histological diagnosis following radical prostatectomies act as the gold standard and „teacher data“. Histological analysis is usually accepted as gold standard; nevertheless it is subject to error [19]. The concentration of the PSA in the patient’s blood and the results of the digital rectal examination have also been recorded for cross validation reasons.

The PSA values of the patients were in the range of 1 ng/ml to 93 ng/ml. 17 patients had a PSA value greater than 20 ng/ml, which is a good indicator for the presence of prostate cancer. 21 patients had a PSA value between 20 ng/ml and 10 ng/ml, which still stands for a certain probability of prostate cancer. The greatest amount of patients, 49 in total, had a PSA value between 10 ng/ml and 4 ng/ml, an amount that makes concluding rather unreliable [43]. 9 patients had a PSA value below 4 ng/ml. No PSA values have been recorded for 4 patients.

Taking a look at the results of the digital rectal examination, about 44 patients had to be diagnosed T3, 41 patients were diagnosed T2 and 11 patients received a diagnosis of T1. One patient was diagnosed T4. No carcinoma could be diagnosed by digital palpation in 3 cases.

The RF datasets have been divided as described above resulting in a sum of 129,967 benign and 40,517 malignant ROIs.

After prostatectomy, a minimum of three prostate slices has been dissected for each patient while keeping the angle of the slices according to the angle of the ultrasound transducer during the data acquisition. Prostate tissues have been stained and marked on the prostate slices with hematoxylin and eosin. Malignant areas have been encircled by the pathologists (Fig. 2). The contours have been transferred to the PC by experi-
ences physicians thus making a more or less definite assignment of dataset ROIs to tissue classes possible (Fig. 3). For transferring the contours to the PC, the B-mode images of all recorded datasets of one patient are displayed on the PC screen. The physician chooses the datasets that fit the prostate slices best and transfers the contour to the PC, interactively encircling the prostate and cancerous areas with the mouse. Only datasets that exactly match the prostate slices are kept for further processing. This results in approximately two or three validated datasets per patient.

For classification reasons the tumors have been divided into two different classes. The first class P1 (positive) consists of all tumors that were visible in the classical B-mode image. All in all this class consists of 27,608 ROIs. Hypoechoic tumors have been included in this class as well as hyperechoic tumors. The second class P2 consists of all isoechoic tumors, which are tumors that are not visible in the conventional B-mode [9, 43]. That means these tumors appear in the B-mode image in the same manner as healthy tissue. Overall 12,909 ROIs belong to this class. Considering these amounts it can easily be concluded that about 1/3 of all tumors cannot be seen in conventional B-mode imaging. This result correlates with former studies on transrectal ultrasound imaging. Prior work has shown that partitioning of the entire amount of malignant ROIs into these two classes improves the classification results considerably [34].

The third class N (negative) consists of all other kinds of tissue. Next to ROIs of normal tissue also ROIs that consist of benign prostate hyperplasia belong to this class. Combining all kinds of tissues that do not belong to one of the two positive classes into one negative class is considered a good choice by means of designing a neuro fuzzy inference system. It has to be mentioned that also all other kinds of tissue, for example stones etc., belong to the class N. The manual transfer of prostate and tumor contours from prostate slices to the PC screen is a procedure that is very sensitive to errors. The physician has to work properly and precisely to keep transfer errors as low as possible during the training procedure. The transferring procedure can be conducted reasonably well for tumors that are more or less visible in the conventional B-mode image, but requires great skills from the physician in case of isoechoic tumors, thus allowing the physician only to use typical landmarks like the prostate border, stones and the seminal duct to navigate. During the preparation, prostate slices often are deformed making a proper correlation even more complicated. From the current point of view, an automatic transfer procedure, based on acquiring images of the histological prostate slices by using a scanner and digital image processing does not seem to be able to satisfy the demands that are required.

### Table 4. Final classification results of FIS using leave-one-out cross validation for both groups, P1 and P2.

<table>
<thead>
<tr>
<th>Parameter group</th>
<th>P1</th>
<th>P2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral and texture parameters</td>
<td>0.861</td>
<td>0.840</td>
</tr>
<tr>
<td>Texture parameters</td>
<td>0.742</td>
<td>0.703</td>
</tr>
</tbody>
</table>

For classification reasons the tumors have been divided into two different classes. The first class P1 (positive) consists of all tumors that were visible in the classical B-mode image. All in all this class consists of 27,608 ROIs. Hypoechoic tumors have been included in this class as well as hyperechoic tumors. The second class P2 consists of all isoechoic tumors, which are tumors that are not visible in the conventional B-mode [9, 43]. That means these tumors appear in the B-mode image in the same manner as healthy tissue. Overall 12,909 ROIs belong to this class. Considering these amounts it can easily be concluded that about 1/3 of all tumors cannot be seen in conventional B-mode imaging. This result correlates with former studies on transrectal ultrasound imaging. Prior work has shown that partitioning of the entire amount of malignant ROIs into these two classes improves the classification results considerably [34].

The third class N (negative) consists of all other kinds of tissue. Next to ROIs of normal tissue also ROIs that consist of benign prostate hyperplasia belong to this class. Combining all kinds of tissues that do not belong to one of the two positive classes into one negative class is considered a good choice by means of designing a neuro fuzzy inference system. It has to be mentioned that also all other kinds of tissue, for example stones etc., belong to the class N. The manual transfer of prostate and tumor contours from prostate slices to the PC screen is a procedure that is very sensitive to errors. The physician has to work properly and precisely to keep transfer errors as low as possible during the training procedure. The transferring procedure can be conducted reasonably well for tumors that are more or less visible in the conventional B-mode image, but requires great skills from the physician in case of isoechoic tumors, thus allowing the physician only to use typical landmarks like the prostate border, stones and the seminal duct to navigate. During the preparation, prostate slices often are deformed making a proper correlation even more complicated. From the current point of view, an automatic transfer procedure, based on acquiring images of the histological prostate slices by using a scanner and digital image processing does not seem to be able to satisfy the demands that are required.

### 4 Results

Two fuzzy inference systems were trained successively using the histological findings as ‘teacher data’. The first system was trained to distinguish the class P1, i.e. hypo- and hyperechoic tumors, from class N, i.e. ‘normal’ tissue. The second system was used to distinguish between the class P2, that is isoechoic tumors, from the class N. Each of both fuzzy inference systems yields a fuzzy value for each ROI of the ultrasound dataset. The fuzzy value is a measure of the probability of a ROI to be malignant or benign. As the classification procedure applied here represents a continuous system, sensitivities and specificities can be chosen freely under dependence on each other.

As can be seen in Table 4, the ROC curve area is $A_Z = 0.86$ for the first system and $A_Z = 0.84$ for the second system, respectively, when using both spectral and texture parameters for the systems. When only texture parameters are used for the training and validation, the ROC curve area is only $A_Z = 0.74$ for the first system and $A_Z = 0.70$ for the second system, respectively. The ROC curve area has been calculated by continuously varying the separation-threshold [38]. The capability of the system has been determined using the leave-one-out classification method, which means that the system has been trained on 99 patients to classify the remaining 100th patient [8]. After 100 single calculations, the results are averaged to form the final classification results.

An overview of different parameter performances is given in Tables 1, 2 and 3. Classification results are calculated for single parameter classification for both target groups P1 and P2, and for a combined classification involving all parameters of a group. This so-called group-classification points out that a single group of parameters cannot achieve the classification results of the final classification involving all groups of parameters.

Next to the classification results of the FIS, the results of a minimum distance classifier (MDC) are presented for comparison. The parameters that were used in the final system are highlighted in the tables.
5 Conclusion

It has been shown that our system for ultrasonic multifeature tissue characterization is able to detect prostate carcinoma with a high grade of accuracy. Thereby, the system can supplement the existing methods of prostate diagnostics to improve the early detection of prostate cancer and allow more reliable diagnostics. As can be seen in Table 4, the ROC curve area is of only $A_{ROC} = 0.86$ for the first system, which was trained to distinguish between hyperechoic, hypoechoic and normal tissue, and $A_{ROC} = 0.84$ for the second system, which was trained to distinguish between isoechoic tumors and normal tissue, respectively. Tumors that are not visible in the conventional B-mode image can be located. Biopsy planning can be improved, unnecessary biopsies can be avoided and performed biopsies can be guided more reliably.

Regarding the classification results as presented in Tables 1, 2, 3, and 4, it is apparent that only the use of spectral parameters can yield satisfying classification results. If only texture parameters are used for the classification, a maximum ROC are of only $A_{ROC} = 0.74$ for the first system and $A_{ROC} = 0.70$ for the second system, respectively, can be achieved using leave-one-out cross validation.

Considering these results, it is obvious that the use of RF data for ultrasonic tissue characterization is essential and cannot be substituted by using video data instead. From video data, only a small subset of parameters, i.e. texture parameters, can be calculated. It has to be mentioned, that all texture parameters used in our approach have been calculated after compensating for the system induced effects and after compensating for attenuation. When video-grabbed data is used instead, the classification results are expected to be even worse.

A comparison of the classification results of the FIS and the MDC classifier confirms the assumption that a nonlinear classifier is needed for the classification of the parameters used in this approach. For single parameter classification, the MDC still performs reasonably well. The advantage of the FIS is apparent, when different parameters are combined in a single system. A combination of different parameters from different parameter groups is only satisfactory when using a non-linear classifier like fuzzy inference systems or neural networks.

The problem with conventional B-mode ultrasound imaging for the detection of prostate cancer is the interobserver variability, i.e. the dependence of diagnostic results on the abilities of the physician [50]. A highly trained physician might be able to detect the majority of tumors, while a novice physician may tend to oversee tumors that are small or have isoechoic properties and can therefore not be seen in conventional B-mode imaging. An ultrasonic tissue characterization system can automate the process of finding suspicious regions and hence can help to reduce the wide gap in ultrasound imaging diagnosis results between expert and novice physicians. As the system evaluates characteristics of the ultrasonic echo signal that cannot be seen in the conventional B-mode image it may also be of great help to the expert. It has to be mentioned that a system for ultrasonic tissue characterization, as far as we can imagine, will not be able to totally replace the expert in finding a diagnosis, but it can significantly assist.

Acknowledgment

This work is an activity of the Kompetenzzentrum Medizintechnik Ruhr (KMR) and was supported by the Deutsche Forschungsgemeinschaft (DFG) grant ER 94/20-2.

References:

Ultrasonic Tissue Characterization for Prostate Diagnostics


